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Systematic Literature Review on EEG-based BCI Applications

Master´s Thesis (15 ECTS)

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Tartu 2020

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Abstract:

Electroencephalography (EEG)-based brain-computer interface (BCI) is a system that provides pathway between the brain and external device via interpreting EEG. EEG-based BCI applications have been initially developed for medical reasons such as enabling patients in completely locked-in state to communicate and rehabilitation of stroke patients. Nowadays EEG-based BCI applications gain increasing significance also in the non-medical domain, where applications are being developed also in order to enable healthy persons to be more efficient, collaborate, develop themselves and much more. The applications in non-medical domain include for example applications for smart home control, monitoring concentration, live brain-computer cinema performance and gaming. The objective of the work is to give systematic overview on the literature on EEG-based BCI applications from the period of 2009 until 2019. In the study the trends in the research have been analyzed. The distribution of the research between medical and non-medical domain has been reviewed and further categorization into fields of research within the domains. In the study also, the equipment used for gathering EEG data and signal processing methods have been reviewed. The systematic literature review has been prepared following the PRISMA model. During the process three well known databases PubMed, Scopus and Web of Science were selected to conduct the publication search. After the initial result, duplicate publications were removed and unique publications further screened and assessed for eligibility. After assessment 202 eligible publications were included in the final analysis. The overall number of articles and conference proceedings has been increasing throughout the years. The amount of research is increasing faster within non-medical domain in comparison to medical domain. The majority of the research has been done in Asia with China contributing the highest number of publications throughout the years. In the study also the overview of the distribution of the EEG based BCI applications among different domains and fields has been given together with techniques and devices used. In the last part of the study current challenges in the field and possibilities for the future have been analyzed.

Keywords:

Electroencephalography (EEG), brain-computer interface (BCI), rehabilitation, systematic literature review

CERCS:

T115 Medical technology

Elektroentsefalograafial põhinevate aju-arvuti liideste rakenduste süstemaatiline kirjanduse ülevaade

Lühikokkuvõte:

Elektroentsefalograafial (EEG) põhinev aju-arvuti liides (AAL) on süsteem, mille abil on võimalik ühendada aju arvutiga ning võtta arvutil EEG vahendusel vastu aju käsklusi. EEG-põhised AAL-rakendused on algselt välja töötatud meditsiinilistel eesmärkidel võimaldamaks näiteks patsientidel sisselukustussündroomi korral suhelda või insuldihaigete rehabilitatsiooniks. Tänapäeval omandavad EEG-põhised AAL-rakendused üha suurema rolli ka mittemeditsiinilises valdkonnas, kus rakendusi arendatakse ka selleks, et terved inimesed saaksid olla tõhusamad, teha koostööd, ennast arendada ning paljudeks teisteks võimalusteks. Mittemeditsiinilises valdkonnas on arendatud näiteks rakendused nutikodu seadmete juhtmiseks, inimese keskendumise tuvastamiseks, osalemiseks interaktiivsel audiovisuaalsel üritusel ning mängimiseks. Käesoleva töö eesmärk on anda süsteemne ülevaade EEG-põhiseid AAL-rakendusi puudutavast teaduskirjandusest ajavahemikus 2009 kuni 2019. Töös on analüüsitud antud uurimisvaldkonna suundumusi, varasema teadustöö jaotust meditsiinilise ning mittemeditsiinilise valdkonna vahel ning jaotust täpsematesse kategooriatesse mõlemas eelpool toodud valdkonnas. Antud on ülevaade seadmetest, mida kasutatakse EEG andmete kogumiseks ning signaalitöötlusmeetoditest. Süstemaatilise kirjanduse ülevaate koostamisel on lähtutud PRISMA mudelist. Protsessi käigus valiti otsingu teostamiseks kolm tuntud andmebaasi PubMed, Scopus ja Web of Science. Pärast esialgseid otsingutulemusi eemaldati tulemuste hulgast korduvad publikatsioonid, viidi läbi skriining ning hinnati täiendavalt publikatsioonide sobivust. Pärast hindamist kaasati lõplikku analüüsi 202 publikatsiooni. Publikatsioonide koguarv antud uurimisvaldkonnas on aasta kohta aastate jooksul kasvanud. Võrreldes meditsiinivaldkonnaga kasvab mittemeditsiinivaldkonnas läbiviidavate uuringute hulk kiiremini. Suurem osa uuringutest on läbi viidud Aasias, kus läbi aastate kõige rohkem publikatsioone on avaldatud Hiinas. Samuti on antud käesolevas töös ülevaade EEG-põhiste AAL-rakenduste jaotusest erinevate valdkondade ja täpsemate kategooriate vahel ning varasemas teadustöös kasutatud tehnikatest ja seadmetest. Töö viimases osas on antud ühtlasi ülevaade uurimisvaldkonna praegustest väljakutsetest ning tulevikuvõimalustest.

Võtmesõnad:

Elektroentsefalograafia (EEG), aju-arvuti liides (AAL), rehabilitatsioon, süstemaatiline kirjanduse ülevaade

CERCS:

T115 Meditsiinitehnika

Contents

1. Introduction

Electroencephalography (EEG)-based brain-computer interface (BCI) is one of the most rapidly developing field of BCI [1], [2] which has potential to expand far beyond the domain of medical applications initially most popular in this field of research. The applications of the EEG-based BCI range from assistive technology, rehabilitation, communication and assessment to monitoring, machine control, authentication and entertainment. The examples include applications developed for robotic arm movement [3], intelligent wheelchair driving system [4], communication for completely locked-in state patients [5], [6], monitoring mental fatigue [7], authentication of persons based on visual stimuli of geometric shapes [8], driving car in a virtual city [9] or recommendations for music based on person`s mood [10] and many others.

The BCI applications are developing quickly and therefore it is important to have up-to-date overview on the EEG based BCI applications together with analysis concerning possible challenges and way forward. The significance of the current study is to give overview about current work done in the field of EEG based BCI applications together with challenges and future possibilities. The study provides comprehensive summary of recent work done in the field.

While preparing the systematic literature review on EEG-based BCI applications the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) model and principles developed by Moher et al. [11] have been followed. In addition to PRISMA model guidance from Cochrane Collaboration could be followed as alternative good practice for preparing systematic literature review [12]. As the PRISMA model has been developed together with the Cochrane Collaboration and with wide number of experts in the field PRISMA model was selected as currently best collection of principles for conducting systematic literature review. The PRISMA principles comprise of 27 aspects that need to be considered during preparation of the systematic review. The PRISMA model has been used as best practice for many previous studies conducting systematic literature review [13]–[16].

During the current study the literature on EEG based BCI applications during the period from 2009 until 2019 was analyzed. The overview concerning the published articles as well as conference papers has been shown throughout the years. The trends regarding the number of publications per year and per publication type has been analyzed. The regions and countries in the forefront of the scientific progress have been highlighted and during the study also the number of publications per author has been analyzed and the results have been shown in the results section.

The overall review of EEG based BCI applications has been created and the BCI applications have been categorized based on domain (medical or non-medical) and by field describing in more detail the current trends in BCI applications development. The study introduces the current trends for development of EEG based BCI applications. Although the initial need for BCI applications has been in the medical domain the study shows that currently higher pace of development is ongoing in non-medical domain. The initial BCI application development has started from the need to allow locked in patients to communicate with others and possibly take part in daily life via control of computer and external devices via brainwaves and is moving currently towards widespread use in daily life of ordinary people with applications monitoring their attention, supporting their daily activities or used for entertainment.

In the study also EEG signal acquisition and processing is analyzed. The overview concerning the prevalence of different EEG devices has been given together with the details regarding number of EEG channels used in previous studies. Overview is given concerning the techniques used for obtaining the EEG data. Regarding EEG signal processing feature extraction and classification methods have been analyzed.

The study gives also detailed overview about current obstacles that inhibit current progress both technically and in other aspects. As important as technical aspects are the ethical, legal and safety considerations on BCI application development. The synthesis on current challenges gives comprehensive map on what to focus in order to support BCI development and shows where are possible risks we would need to address. The study also shows direction where the development is moving and possibilities for the future. The trends and future possibilities give better understanding what we could expect after years to come.

2. Background

In this chapter the discoveries in brain research and technology are discussed that have made the development of EEG-based BCI applications possible. Overview concerning the functioning of BCI is given together with possible different categorizations of BCI-s. In the last part of the chapter the need and possible use of BCI applications is explained and BCI applications in medical and non-medical field introduced.

2.1 Electroencephalography (EEG)

The use of EEG has become possible due to the work and discovery by Hans Berger who discovered in 1924 that electrical signals could be measured from the scalp of human brain [17]. The initial discovery was done using simple galvanometer and confirmed the possibility that neural activity could be measured by this method [18]. Berger conducted his work using invasive methods and was able to also identify already then EEG waves present in a brain such as alpha wave and therefore it is also known as Berger`s Wave [19].

Table 1: Brainwaves, frequency ranges and description according to Ramakuri et al. [20] and Landavazo and Nandikolla [21].

Brainwave		Frequency	Description
Delta		0-4 Hz	Deep, dreamless, non-REM sleep, unconsciousness
Theta		4-8 Hz	Intuitive, recall, fantasy, imaginary, dream
Alpha		8-13 Hz	Relaxed, but not drowsy, tranquil, conscious
Beta	low beta	13-15 Hz	Relaxed yet focused, integrated
	midrange beta	16-20 Hz	Thinking, aware of self and surroundings
	high beta	20-30 Hz	Alertness, agitation
Gamma		over 30 Hz	Observed during short term memory

EEG measures the brain electrical activity caused by flow of electric currents during synaptic excitations of neuronal dendrites and is measured via electrodes located on the scalp [1], [18]. After the initial discovery by Hans Berger additional brainwave types and mental states associated with the brainwave types have been determined. The detailed overview concerning each brainwave type, their frequency range and associated mental states has been given in Table 1.

2.2 Brain Computer Interface (BCI)

BCI is a system that provides pathway between the brain and external device enabling to read biological signals and interpreting certain aspects of the person´s cognitive state [13]. BCI could be used by a person to control computer or other device via computer by one`s thoughts without using ordinary methods of working with computer (e.g. using hands) [22]. BCI could be used also to monitor subject´s mental states such as emotions [23], concentration [24] or drowsiness [25].

BCI is functioning generally by four distinct processes comprising of converting biological signals into electrical signals for the computer, extracting features, gathering important information and combining information for useful purposes [20]. The EEG signal analysis has been further divided into four steps such as gathering of raw EEG data, signal pre-processing, feature extraction and classification [2].

According to Padfield et al. [2] the signal analysis steps could be characterized as described below. The collected raw EEG data comprises of all the EEG data collected before pre-processing and further analysis. After collection of raw EEG data pre-processing is used to clean noise and enhance the quality of collected EEG data for further analysis. During feature extraction discriminative and non-redundant information is extracted from the EEG data to form a set of features. Padfield et al. have highlighted that during this signal processing step features are determined on which classification can be carried out. Extracted features will capture distinct signal characteristics which can be used as a basis for the differentiation between task-specific brain states. During classification step it is determined which mental task has been carried out by the subject and corresponding actions are taken by the system. The use of specific feature extraction and classification method depends on specific type of BCI application under study.

2.3 Categorization of BCI-s

The most common way to categorize BCI is on the basis of invasiveness. The BCI could be invasive or non-invasive depending whether the device is connected physically to one´s brain and the electrodes are placed inside the brain or the device will read brainwaves from top of scalp [1]. The use of invasive method of direct contact of the electrodes with brain is more efficient as there are less interfering factors that influence the signal quality [26], but the invasive method engulfs the risks of surgical procedures and possible related complications.

More popular and easy to use is the non-invasive method, where the brainwaves are read from top of scalp for example via electrodes placed near the head in a cap or headset. Although this method has also some drawbacks including disturbance from external noise, effects from the posture and mood of the subject and in detecting signal not in high strength and therefore with reduced signal quality [2] there are many studies ongoing to determine best ways for signal detection and analysis.

The currently most popular non-invasive method for acquiring brainwaves for BCI is detection through EEG. The popularity of EEG is supported by inexpensiveness of the equipment, less complications, portability, easy process to set-up and use and possibility to directly measure neural activity [1], [2]. EEG reading is easy to use and has high potential to be applied by majority of the population in order to use high variety of possibilities that BCI could give. Other non-inavsive methods include functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG) and near-infrared spectroscopy (NIRS) which can be used separately or combined [1].

BCI could be divided into separate subgroups based on the way to detect and convey the signal from the brain to BCI application and principles of the functioning of the BCI. As per Al-Nafjan et al. [13] BCI-s could be categorized active or passive based on the control of the BCI application. The categorization of BCI-s based on active or passive control and corresponding techniques used to obtain EEG data have been presented in Table 2.

The BCI-s using active control react on conscious efforts to alter brainwave patterns and the applications could be controlled via active efforts by the user. The BCI-s applying passive control react to involuntary status of the brainwaves, for example on emotional states such as meditation, excitement and stress [13]. During active control of the BCI application the signal could be detected via different techniques. The field of different techniques is broad and is covering motor imagery, external stimulation (such as visual, auditory and vibrotactile), error-related potential, hybrid and other techniques [1].

Table 2: Categorization of BCI-s as and corresponding techniques used to obtain EEG data according to Al-Nafjan et al. [13] and Abiri et al. [1].

Category	**Technique used to obtain EEG data**	**Description**
Active	Motor-imagery	Imagining of the movement of specific body part for example hands, feet or tongue. The intent will affect the brain activity and could be detected from the EEG. The imagination activates the brain areas that are responsible for generating the actual movement.
	Visual evoked potential	The brain activity is affected by external visual stimulation and the corresponding altered EEG activity is registered. For example in case of steady-state visual evoked potential (SSVEP) there are different visual stimuli flickering at different frequencies and depending on the direction of the gaze of the subject the EEG pattern will be consistent with the specific flickering rate.
	Auditory evoked potential	Auditory stimulation is generated and depending on the focus of the subject corresponding EEG activity is registered.
	Vibrotactile evoked potential	Physical vibrations at different frequencies are generated for example on the hands and feet of the subject. Depending on the focus of the subject corresponding EEG pattern to the specific physical vibration is registered and could be used to control some external device.
	Imagined speech	Imagination of words or sentences that are recognized from EEG.

	Error related potential	The error related potential is generated when there is mismatch between subject´s intentions and response from the BCI application. The technique can be used to correct tasks given by the subject. For example when the subject is controlling cursor, but the cursor is moving to wrong direction error related potential is generated and the course of the cursor can be corrected.
Passive	Analyzing EEG spectral changes	Monitoring dowsiness, attention, mental workload, emotions, concentration and other states of the mind.

As per Pasqualotto et al. [15] and Machado et al. [27] BCI could be also categorized depending whether BCI is dependent or independent of certain muscle movement. Padfield et al. [2] have also categorized BCI as evoked or spontaneous. As per Nicolas-Alonso and Gomez-Gil [28] BCI could be categorized synchronous or asynchronous. The overview concerning additional different categorization of BCI-s in the literature and descriptions have been presented in Table 3.

Dependent BCI-s require muscle control for example via gaze control. Independent BCI on the other hand detect signals only based on changes in the brainwaves without required muscle movement [15], [27]. According to Padfield et al. [2] another possibility to categorize BCI-s would be depending on whether external stimulation is required for the functioning of the BCI or not dividing the systems into evoked when external stimulation is needed and to spontaneous in case external stimulation is not needed. According to the aforementioned categorization by Padfield et al. evoked systems include for example steady-state visual evoked potential (SSVEP), where visual stimulation is received via flickering at unique frequencies that causes corresponding changes in EEG when focusing on specific stimulus at specific flickering frequency. According to this categorization spontaneous systems include for example motor-imagery technique, where external stimulation is not needed and the changes in EEG patterns are generated via imagining movement of a limb. Padfield et al. have noted that the categorization to evoked and spontaneous systems has been also named by some authors as exogenous and endogenous.

Table 3: Additional different categorization of the BCI-s in the literature.

Author	BCI categorization	Description
Pasqualotto et al. [15] Machado et al. [27]	Dependent	Dependent on muscles and peripheral nerves. As an example in case of visual evoked potential (VEP) gaze is directed by muscles to focus on different visual stimuli.
	Independent	Muscle movement is not needed in order to control BCI. For example in case P300 response is detected from EEG and analyzed.
Padfield et al. [2]	Evoked	Also named as exogenous. Some type of external stimulation required such as visual, auditory or sensory. Can be further divided to evoked potentials and event related potentials. In case of evoked potentials changes in EEG can be detected due to responses to external stimuli. In case of event related potentials the changes in EEG are caused by sensory or cognitive events.
	Spontaneous	Also named as endogenous. External stimulation is not required. As an example motor-imagery technique, where subjects imagines movement of a limb and there is no additional input as external stimuli.
Nicolas-Alonso and Gomez-Gil [28]	Synchronous	The BCI analyzes signals during certain time windows and the subject is able to give commands after fixed time intervals.
	Asynchronous	The brain waves of the subject are analyzed constantly and the subject can give commands whenever the subject wants. Asynchronous BCI gives the subject more possibilities and flexibility concerning controlling the BCI.

An additional way to classify BCI-s is based also on the time when the signals from the user are gathered by the BCI. The BCI-s could be therefore divided as synchronous and asynchronous [28]. BCI is considered synchronous, when the information concerning the brainwave status is gathered during specific time intervals. It means that the user can give commands only at distinct timing and the brainwaves are not measured during other times.

In case of asynchronous analysis the brain patterns are analyzed on ongoing basis and the user is more flexible when giving commands to the system.

2.4 BCI applications

The BCI applications have been initially developed to help people with disabilities to be able to communicate, control computers and use aiding equipment such as wheelchair or robotic arm. One of the first BCI applications assisted individuals with speech anomalies and the possibility of using BCI to develop prosthetic arms was considered as early as 1917 [1], [13]. The applications have been used by people suffering from locked-in syndrome or amyotrophic lateral sclerosis (ALS) [1]. The applications have been applied also in case of paralysis, amputations and loss of central nervous system functionality due to other reasons [2]. BCI could be applied in order to enhance neuroplasticity [29] or develop wearable lower-limb exoskeletons [30].

BCI applications could have wide range of possibilities for use in addition to medical applications. EEG based BCI applications have been used in different fields stretching from medical devices to BCI applications used for entertainment, art and many others [13], [20], [22]. The applications for entertainment could include games designed for improving subject attention level or concentration level [20], but also control of drones and humanoid robots [22].

In addition to medical devices helping people to cope with daily tasks promising direction for BCI applications is the monitoring of brain activity in order to ensure the safety at the workplace and in traffic. There have been studies developing devices to monitor the alertness level of employees [31]. Additional aspect is the overall car traffic safety and avoidance of driving fatigue and drowsiness during driving that could result in fatal accidents [1]. BCI applications can be used for controlling smart home [32]–[35] or a car [9], [36]. In the domain of non-medical applications the BCI could be also used for sport motor skills improvement, acting skills improvement or surgical skills improvement [29].

The field of possible applications for EEG based BCI is vast and in development with high pace. In the effort of developing better and more diverse BCI applications researchers from many different disciplines such as neurobiology, rehabilitative engineering, psychology, computer science, mathematics, medical physics and biomedical engineering have joined efforts in order to address the needs of different subject populations [13].

In order to better detect brain activity and improve the accuracy of BCI applications additional methods for brain activity measuring could be used in addition to EEG. During recent years work has been done in order to develop hybrid paradigm which could combine two or more methods of detecting brainwaves. EEG could be combined with heart rate, eye movements (EOG), hemodynamic signal recording through functional near-infrared spectroscopy (fNIRS) or functional magnetic resonance imaging (fMRI) [1], [37].

In the current study we have divided the BCI applications by application domain to medical or non-medical applications and further divided the BCI applications within the domains by fields. The medical domain contains the fields of assistive, communication, monitoring, rehabilitation, assessment and other and the non-medical domain contains the fields of monitoring, control machine, entertainment, assistive, authentication, communication and other.

The number of articles in the field of EEG-based BCI is increasing with higher volume of the articles published in respected journals such as Transactions on Neural Systems and Rehabilitation Engineering (IEEE), Journal of Neural Engineering (IOPScience), Frontiers in Human Neuroscience (Frontiers) and Biomedical Signal Processing and Control (Elsevier). There is number of conferences in the field of BCI where high number of important studies on the EEG-based BCI applications have been presented such as Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), International IEEE/EMBS Conference on Neural Engineering (CNE), International Winter Workshop on Brain-Computer Interface (BCI), Annual International Conference of the IEEE Engineering in Medicine and Biology Society and International Conference on Neural Information Processing.

3. Objectives

During the preparation of the systematic literature review concerning EEG-based BCI applications, objectives were set for the study based on the general need for systematic literature review on the topic. The systematic literature review was prepared based on three databases PubMed, Web of Science and Scopus in order to obtain wide range of reliable peer reviewed publications on EEG-based BCI applications [13], [14], [16]. After identification of the publications and subsequent screening and eligibility process as per PRISMA model 202 publications that passed eligibility process were included in the final analysis to address the set objectives. Below have been listed the objectives set for conducting the systematic literature review.

The objectives of the systematic literature review on EEG-based BCI applications:

1. Determine the trends concerning publication of articles, conference proceedings and overall number of publications on EEG based BCI applications from 2009 until 2019.
2. Analyze by regions and countries which regions and countries are in the forefront of scientific progress concerning EEG based BCI applications and highlight the most contributing authors on the topic.
3. Determine the proportion of scientific studies conducted on the topic in the medical and non-medical domain and further analyze the distribution of the studies per application field.
4. Give overview concerning the devices used for EEG signal collection and specify the number of EEG channels used for obtaining the data.
5. Determine the techniques used for obtaining EEG data and give overview concerning the trends in signal processing including feature extraction and classification methods.

4. Methods

The preparation of systematic literature review takes time and discipline as there need to be principles to obey during the preparation process. When preparing for the systematic literature review, a number of examples of previous systematic literature reviews conducted in various research topics were reviewed. Some of the literature reviews stood out among the others for being more structured and well designed. As per best practice PRISMA model has been used to guide the conduct of systematic literature reviews in many fields of research [11], [38]. In addition to PRISMA model the guidance from Cochrane Collaboration can be followed in order to prepare systematic literature review [12]. As the PRISMA model has been developed together with the Cochrane Collaboration and with wide number of experts in the field PRISMA model was selected as currently best collection of principles which to use in order to conduct current systematic literature review on EEG-based BCI applications. The PRISMA method has been developed by Moher et al. [11] and has been used widely in conducting well organized systematic literature reviews in many studies [13]–[16].

4.1 PRISMA model

In order to set general guidelines and increase the quality of systematic reviews and meta-analyses Moher et al. [11] have developed set of 27 aspects that should be considered when preparing systematic reviews and meta-analyses. The set of guidelines was developed in 2009 and called PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). The guidelines have been created based on previous version of the guidelines from 1996 called QUOROM (QUality Of Reporting Of Meta-analyses). The PRISMA model is unique in the way that the model has been developed throughout the years in collaboration with wide number of experts in the field. The model is voluntary to use, but over 170 journals worldwide endorse the use of PRISMA model for publishing systematic literature review [39].

Table 4: PRISMA checklist for preparing systematic reviews based on Moher et al. [11].

Sub-topic number	Topic and sub-topic in PRISMA checklist	Description
	Title	
1	Title	Publication identified as systematic review, meta-analysis or both.
	Abstract	
2	Structured summary	Provide structured summary including as applicable: background, objectives, data sources, eligibility criteria, conclusions and results.
	Introduction	
3	Rationale	Describe the rationale for the publication.
4	Objectives	Provide the questions being addressed in the study.
	Methods	
5	Protocol and registration	Indicate if review protocol exists and if available. Provide registration information and registration number in case available.
6	Eligibility criteria	Specify characteristics used as eligibility criteria.
7	Information sources	Describe the information sources where the publications were obtained and date searched.
8	Search	Present electronic search strategy for at least one database.
9	Study selection	State the process of study selection including screening and eligibility.
10	Data collection process	Describe the method of data extraction from the publications.
11	Data items	List and define all variables for which data were sought.
12	Risk of bias in individual studies	Describe assessing risk of bias of individual studies.
13	Summary measures	State the summary measures.
14	Synthesis of the results	Describe the methods and of handling data and combining results of studies.
15	Risk of bias across the studies	Specify any assessment of risk of bias that may affect the cumulative evidence.
16	Additional analyses	Describe methods of additional analyses (if done).

	Results	
17	Study selection	Provide number of studies screened, assessed for eligibility and included in the review.
18	Study characteristics	Present the characteristics for which data were extracted.
19	Risk of bias within studies	Data on risk of bias of each study, if available (see also item 12).
20	Results of individual studies	Present for each study simple summary data for each intervention group and effect estimates (if applicable).
21	Synthesis of results	Present results of each meta-analysis done.
22	Risk of bias across studies	Present results of any assessment of risk of bias across studies (see also item 15).
23	Additional analysis	Give results of additional analyses, if done.
	Discussion	
24	Summary of evidence	Summarize the main findings.
25	Limitations	Discuss limitations at study and outcome level (e.g. risk of bias).
26	Conclusions	Provide general interpretation of the results and implications for future research.
	Funding	
27	Funding	Describe sources of funding for the systematic review.

The PRISMA model has been well accepted for preparing systematic reviews and meta-analyses. The further updated material concerning PRISMA model is also stored the PRISMA official web page http://www.prisma-statement.org/ and kept updated with additional comments and news. The overview concerning the PRISMA checklist for preparing systematic reviews and meta-analyses has been presented in Table 4.

4.2 Information sources

The publications concerning EEG-based BCI applications can be found from high number of different sources. In the frame of current study three well known databases PubMed (https://pubmed.ncbi.nlm.nih.gov/), Scopus (https://www.scopus.com/) and Web of Science (http://login.webofknowledge.com/) were selected to conduct the publication search [13], [14], [16]. Search was conducted in the databases PubMed, Scopus and Web of

Science using basic search settings with the below described search terms relevant for current study.

The search was conducted in PubMed database on 20th of October 2019 with the search term („electroencephalography based“ OR „EEG based“) AND („brain computer interface“ OR „BCI“ OR „brain machine interface“ OR „BMI“) AND („application“ OR „applications“). The search resulted in 185 publications that were then included for further screening. The search in the Web of Science database was conducted on 28th of October 2019 with the search term („electroencephalography based“ OR „EEG based“) AND („brain computer interface“ OR „BCI“ OR „brain machine interface“ OR „BMI“) AND („application“ OR „applications“) and the search in Web of Science database resulted in 451 publications. The search in the Scopus database was conducted on 30th of October 2019 using search term (“electroencephalography based” OR “EEG based”) AND (“brain computer interface” OR “BCI” OR “brain machine interface” OR “BMI”) AND (“application” OR “applications”) and 569 publications were identified through the search for inclusion to further screening.

During the identification of the publications via parallel searches in PubMed, Web of Science and Scopus databases all together 1205 publications were listed. As the search from three different databases resulted in number of duplicates that were represented in two or more database searches the duplicates were removed and one unified listing of the publications created. After database searches and removal of duplicate publications the process resulted in 635 publications for further analysis for screening and eligibility assessment. The example concerning the details collected during screening has been shown in Table 5.

Table 5: Example of details collected during screening.

Number	Title of the publication	Corresponding author	Country	Journal or conference name	Keywords	Abstract	Year published	PubMed	Web of Science	Scopus
1	A EEG-based emotion re	Yan Jianzhuo	China	Brain Informatics (Sprir	EEG; Emoti	As an adv	2019	PubMed		Scopus
2	Online home appliance	Kim Minju	South Ko	Electronics (MDPI)	Brain–com	Brain–cor	2019			Scopus
3	An Asynchronous Hybrid	Yu Yang	China	Transactions on Neural	Brain comp	In this pa	2019		WoS	Scopus
4	EConHand: A Wearable	Qin Zhun	China	International IEEE/EMB	Electroenc	Brain-Cor	2019		WoS	Scopus
5	Using EEG-based brain c	Jeunet Camille	France	Neurophysiologie Clinic	ADHD; Brai	Many Bra	2019	PubMed	WoS	Scopus
...	...	...	...	...	...	...	...	...	...	...
631	Towards ambulatory bra	Lotte Fabien	France	5th Advances in Compu	Brain-Com	Brain-Cor	2009			Scopus
632	P300 detection based o	Chumerin Nikol	Belgium	Annual Conference on	Amyotroph	We propo	2009		WoS	Scopus
633	A feasibility study of no	Wang Chuanchu	Singapore	4th International IEEE/	Non-invasi	This pape	2009		WoS	Scopus
634	Interacting with the env	Cincotti Febo	Italy	International Conferen	BCI; EEG; A	The brain	2009		WoS	Scopus
635	EEG-based classificatior	Zhou Jie	USA	Computers in Biology a	Electroenc	The ultim	2009	PubMed	WoS	Scopus

In the current review the amount of different studies reviewed was 635. The number of studies included in the final analysis was 202. Due to high number of studies included in the review the possible bias of individual studies was reduced to minimal. The high number of studies involved gives more adequate overview concerning trends for the studies conducted in the field. As per Roy et al. it is valuable to include in the review larger variety of papers including non-peer reviewed papers in order to reduce possible bias that could be introduced during peer-review process, such papers could include more unconventional research ideas and increase the diversity of ideas [14].

4.3 Eligibility criteria

The further selection of the publications for the current study was based on predetermined eligibility criteria. The eligibility criteria were determined in order to filter relevant publications concerning EEG-based BCI applications as per objectives of the study for further analysis. The eligibility criteria were selected according to similar principles used in previous review articles and articles following the PRISMA model [11], [13]–[16].

The following eligibility criteria were applied during review of the publications during screening and eligibility assessment:

- Publications needed to be relatively current. In the further analysis publications were included from the period between 2009 and 2019.
- Excluded meeting abstracts, book chapters, masters and doctoral dissertations and non-English publications.
- Excluded non peer-reviewed journal articles and non peer-reviewed conference proceedings.

During further review there was manual scan conducted for the titles, keywords and abstracts of the publications. Publications were excluded that did not address the subject, but rather mentioned the subject in passing in general. During the review 402 publications were excluded that did not meet the eligibility criteria. The review resulted in 233 publications for further full text assessment of eligibility.

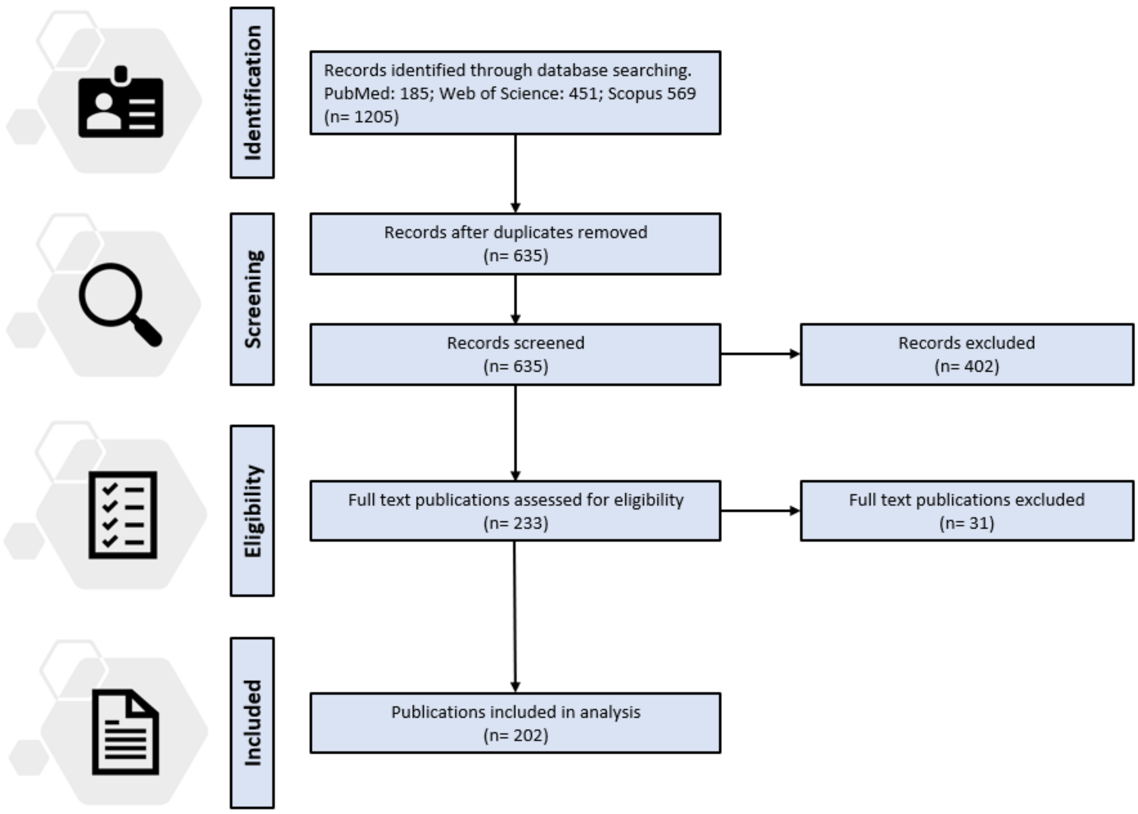

Figure 1: The flow of information during selection of studies according to the PRISMA model.

During the full text review of 233 publications 31 publications were further excluded not corresponding to the eligibility criteria. After all steps of publication selection per PRISMA model, 202 publications were included in the final analysis [1]–[10], [13], [17]–[27], [29]–[36], [40]–[211]. The overview concerning the process of identification, screening, assessing the eligibility and inclusion of the publications in the final analysis as per PRISMA model has been shown in Figure 1.

4.4 Data items extracted from the publications

During the full review of the 202 publications included in the analysis 25 separate data items were extracted from each publication. The 25 separate data items can be categorized in 6 larger categories such as origin of the publication, publication summary, focus of the publication, equipment used, signal processing and reproducibility. The extraction of the data items follows the PRISMA model for preparing systematic literature review and categorization of the data items extracted has been applied also by Roy et al. [14] during similar preparation following the PRISMA model.

The category origin of the publication includes the journal or conference name, corresponding author, country and source for the publication. Category publication summary includes the full title of the publication, abstract available for the publication, keywords, type of publication and year published together with challenges and future possibilities covered in the publication. In the category focus of the publication there have been included data items domain and field that have been used to determine the general focus of the publication and more specific field of application.

Table 6: Data items extracted for each article under analysis.

Category	Data item	Description
Origin of the publication	Journal or conference name	Name of the journal where the article was published or conference where conference proceeding presented.
	Corresponding author	Name of the corresponding author of the publication.
	Country	Location of the university of the corresponding author.
	Source for the publication	Database where the publication was located.
Publication summary	Title of the publication	Full title of the publication.
	Abstract	Abstract available for the publication.
	Keywords	Keywords listed for the publication.
	Type	Type of publication (e.g. experimental, review).
	Year published	Year when the publication was published.
	Challenges	Challenges mentioned in the publication concerning the development of the application or in general on the topic.
	Future possibilities	The possibilities for the future and way forward concerning the application or in general on the topic.
Focus of the publication	Domain	Publication covering medical, non-medical or both domains.
	Field	Publication covering specific field under medical domain, non-medical domain or both domains (e.g. assistive).

Equipment used	EEG device	Device used in the study for collecting EEG data.
	Number of EEG channels	Number of EEG channels applied in the study to gather EEG data.
Signal processing	Signal acquisition	Signal acquisition method.
	Technique	Techniques used for obtaining EEG data (e.g. visual evoked potential).
	Pre-processing	Pre-processing used in the study (e.g. filter).
	Feature extraction method	Feature extraction method used in the study (e.g. power spectral density).
	Feature extraction type	Feature extraction automatic or manual.
	Transfer learning used	If transfer learning used in the study.
	Machine learning used	If machine learning used in the study.
	Machine learning method	Machine learning method used in the study (e.g. linear discriminant analysis).
Reproducibility	Availability of dataset	Dataset used in the study and if dataset available.
	Availability of code	Whether the code used in the study available and where the code could be obtained.

Under the category equipment used there is listed EEG device and number of EEG channels used in specific study. Concerning signal processing there was gathered information covering signal acquisition method, technique used for obtaining EEG data, preprocessing, feature extraction method and type, transfer learning and machine learning method. In addition data concerning availability of the dataset and code was collected in order to have overview concerning the reproducibility of the studies. The data items were captured and stored in separate database for further analysis. The data items extracted from the publications have been presented in detail in Table 6.

5. Results

In this chapter the study results are analyzed. The results have been divided into 10 sections. In the first part of the chapter the sections cover the distribution of articles and conference proceedings per year, publications per country, experimental publications per year, publication distribution by domain and number of publications per author. The sections in the second part of the of the chapter focus on EEG devices used, number of EEG channels and on signal analysis in sections techniques used to obtain EEG data, feature extraction and classification.

5.1 Articles and conference proceedings per year

During the period from 2009 until 2019 the overall number of articles and conference proceedings published per year has been gradually rising. In the beginning of the period the total number of the publications has been 11-15 publications per year from 2009 until 2011. During the period from 2012 until 2016 there has been slight increase in the volume of the publications to 16-19 publications when only in year 2014 there has been decrease to 10 publications per year. Significant increase can be noted from year 2017 onwards when the number of publications per year has increase up to 32 publications per year in 2017. Please see overview concerning the number of articles and conference proceedings per year in Figure 2. As the search of the publications was conducted in the three databases during the period from 20th October 2019 until 30th October 2019 the final number of publications for 2019 could have additional slight increase.

The trend concerning increase in the overall number of publications per year has been noted also by Al-Nafjan et al. [13] when analyzing the volume of EEG-based emotion recognition publications. In the aforementioned article there has been shown rapid increase in the overall number of publications on the topic from 2010 to 2016 and suggested that the increase could be caused by increased knowledge of neurobiological processes, computers with faster computational processing, greater availability of devices for recording brain signals and more powerful signal processing and machine learning algorithms. Increase in the number of publications concerning EEG-based BCI-s has been also demonstrated by Hwang et al. [99], where significant increase has been illustrated during the period from 2007 until 2011.

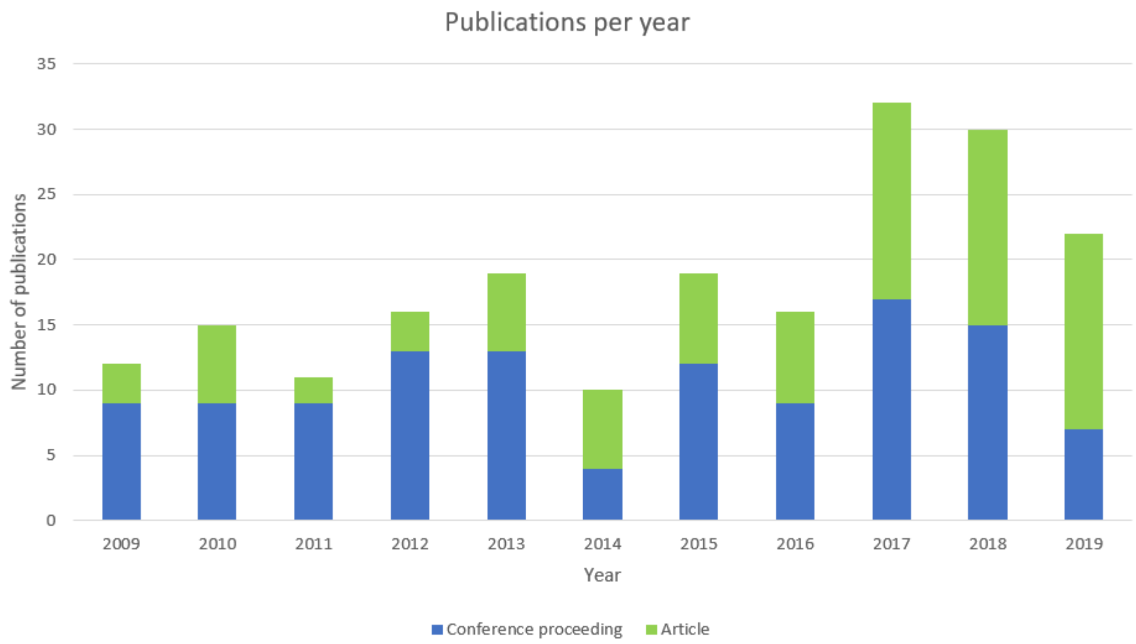

Figure 2: The number of publications per year.

It can be noted from figure 2. that during the period from 2009 until 2019 the overall number of conference proceedings published concerning EEG-based BCI applications has been higher than the number of articles published. Out of the 202 publications there has been 117 conference proceedings (58% of the publications) and 85 articles (42% of the publications). Although in the years from 2009 until 2016 the number of conference proceedings has been greater than the number of published articles (except for year 2014) trend has been noted for recent years concerning the increase in the relative volume of the published articles.

The reason why the proportion of articles has been increased over the recent years could be the overall development of the technology making it more easy and efficient to conduct the research on EEG-based BCI applications and inclusion of the topic more in the articles. In the beginning of the period under current focus the higher variety and number of publications was included in conference proceedings. This trend noted in the current study illustrates the observation done by Roy et al. [14] noting that there would be more wide variety of research ideas within different repositories and among different type of publications. The effect highlights the need to include in the literature review higher variety of repositories and different type of publications in order to include objective coverage of the research ideas on the topic and avoid possible publication bias.

5.2 Publications per country

The distribution of the publications concerning EEG-based BCI applications were further analyzed by countries. Out of the 202 publications analyzed highest number of publications on the topic has been published in China (39 publications). The other countries where 10 publications or more have been published on the topic during the period from 2009 until 2019 are USA (23 publications), India (18 publications), Singapore (11 publications), South Korea (11 publications) and Taiwan (10 publications). It is interesting to note that among the 6 countries 5 of them are located in Asia. Similar results have been found also by Hwang et al. [99] and Roy et al. [14] where USA and China have dominated as the countries with highest number of publications on EEG-based BCI. The detailed overview concerning the publications per country has been presented in Figure 3.

All together 37 different countries have contributed with publications on EEG-based BCI applications within the time period reviewed. Highest number of countries have contributed from Europe, where there have been publications from 18 different countries with Germany and Italy contributing most (both 9 publications). From Asia there have been publications from 14 different countries, but the average number of publications per country is significantly higher. As highlighted above most publications per county has been contributed by China. From North America publications have been contributed from three countries: USA, Canada and Mexico. In Australia 7 publications were published, but from South America only in Brazil one publication has been published. It is interesting to note that no publications were prepared from Africa.

As per region 111 publications (55%) have been contributed by Asia being firmly in the leading role concerning number of studies published. In Europe all together 56 studies (27%) have been published during the period. Asia and Europe are followed by North America by 27 publications (13%). The volume of scientific studies on EEG-based BCI applications is less important in Australia (4%) and South America (1%). No studies on the topic were located from Africa for the period under review.

Country	Number of publications
China	39
USA	23
India	18
Singapore	11
South Korea	11
Taiwan	10
Germany	9
Italy	9
Australia	7
Austria	7
UK	6
Japan	5
Saudi Arabia	5
Spain	5
Pakistan	4
Belgium	3
France	3
Switzerland	3
Canada	2

Country	Number of publications
Hungary	2
Indonesia	2
Malaysia	2
Mexico	2
Brazil	1
Bulgaria	1
Croatia	1
Czech Republic	1
Denmark	1
Greece	1
Iran	1
Israel	1
Poland	1
Quatar	1
Romania	1
Slovenia	1
Thailand	1
The Netherlands	1

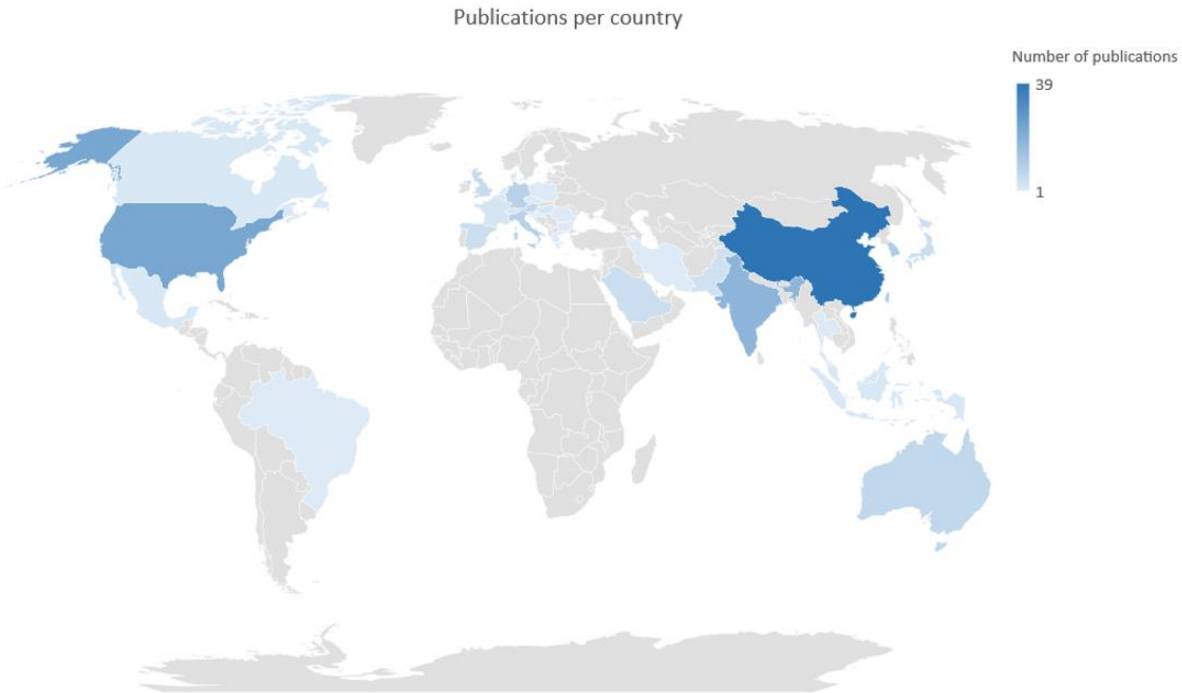

Figure 3: Number of publications per country.

5.3 Experimental publications per year

Among the experimental publications on EEG-based BCI applications non-medical publications have contributed the majority of the experimental publications per year. Exceptional cases from the trend have been seen in 2009 and 2013 when more medical publications were published when compared to the number of non-medical publications per year. Although in general there has been significantly higher number of non-medical publications per year during the period under review during recent years the proportion of medical publications has risen reaching up to 36% of the publications.

During recent years the overall number of experimental publications has been significantly increased from 8-15 publications per year during 2014 until 2016 to 19-25 publications per year during the period from 2017 until 2019. The trend of fast increase in the overall number of publications on EEG-based BCI applications can be seen also from Hwang et al. [99] and the distinctively higher number of non-medical publications per year when compared to medical publications has been highlighted by Al-Nafjan et al. [13] concerning EEG-based BCI for emotion recognition.

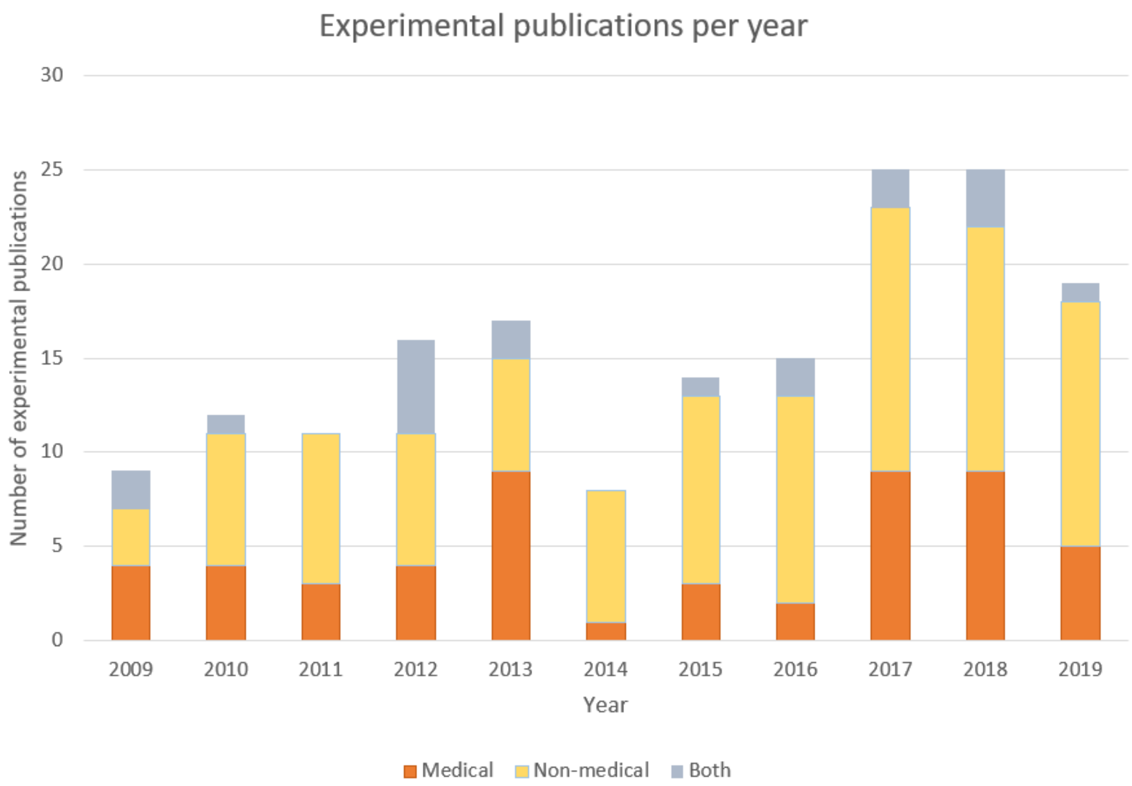

Figure 4: Experimental publications per year.

Through the period analyzed there has been published 99 publications (58% of the publications) in the non-medical domain and 53 publications (31% of the publications) in the medical domain. In 19 cases (11% of the publications) the publications cover both domains. During interpretation of the results it should be also noted that as the database search was conducted during the period from 20th October 2019 until 30th October 2019 the final number of publications for 2019 could have additional slight increase. Please see the overview concerning the number of experimental publications per year in Figure 4.

Although initially the EEG-based BCI applications were mainly developed for medical reasons to help patients to communicate, grasp objects, move around and support in other daily activities the focus has been moving from medical domain also to non-medical applications. The shift in the focus does not reduce the importance of these applications in the medical domain but rather shows the wider potential of EEG-based BCI applications and opens new doors for applying the possibilities wider.

5.4 Publication distribution by domain

Among the publications published within the period from 2009 to 2019 there were 58% of the publications (99 publications) from non-medical domain. In previous study conducted by Al-Nafjan et al. analyzing the EEG-based BCI applications for emotion recognition it was also found that the majority of the studies (77%) were studies within the non-medical domain [13].

In the overall number of publications analyzed 31% of the publications (53 publications) are from the medical domain and the in the additional 11% of the publications (19 publications) both domains have been included. Please see the distribution of the publications per domain in Figure 5. Similar prevalence of publications in medical domain has been determined by Al-Nafjan et al. [13] where 23% of the publications were located in the medical domain.

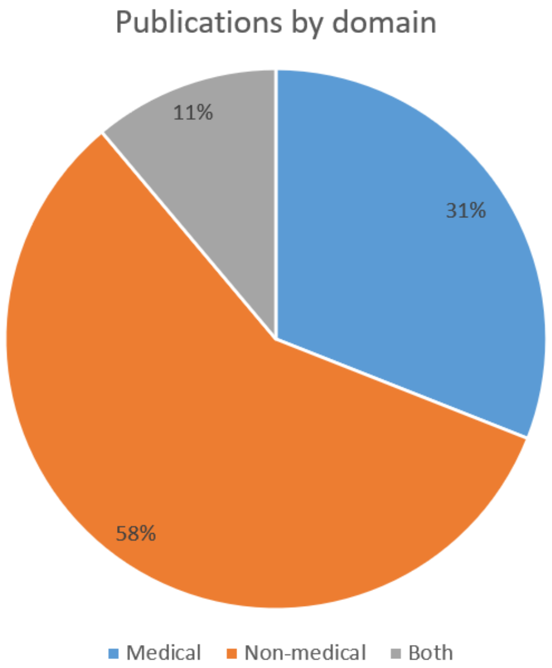

Figure 5: Distribution of publications per domain.

The publications located in the medical domain could be further divided based on the type of applications into fields such as assistive, communications, monitoring, rehabilitation, assessment and other. Within medical domain the field covering assistive applications is the largest contributing 62% of the publications in the domain. The assistive field includes studies on robotic arm movement in medical setting [3], lower-limb prosthesis control [153] and intelligent wheelchair driving system [4]. The next important fields in the medical domain are communication, monitoring and rehabilitation covering 11%, 10% and 9% of the publications in the medical domain respectively.

The communication field contains applications for example for communication of patients in completely locked-in-state [5], [6], but also other applications enhancing the communication possibilities. The publications concerning monitoring include possibility of detecting seizure [170], and monitoring emotional changes in patients [45]. Among studies analyzing possibilities for rehabilitation there is important role for the studies supporting the rehabilitation of stroke patients [72], [180], [208]. The fields assessment and other cover all together 8% of the publications in the medical domain both contributing 4% of the publications in the domain.

The prevalence of different fields in the medical domain differ when compared to previous work of Al-Nafjan et al. [13], as the most popular fields in this domain were then assessment and monitoring. The difference would be explained by the difference in the scope of the studies where in previous case the focus was on emotion recognition based on EEG-based BCI, but in current study we focus on EEG- based BCI applications in general. The overview concerning the publications in the medical domain has been presented in Figure 6.

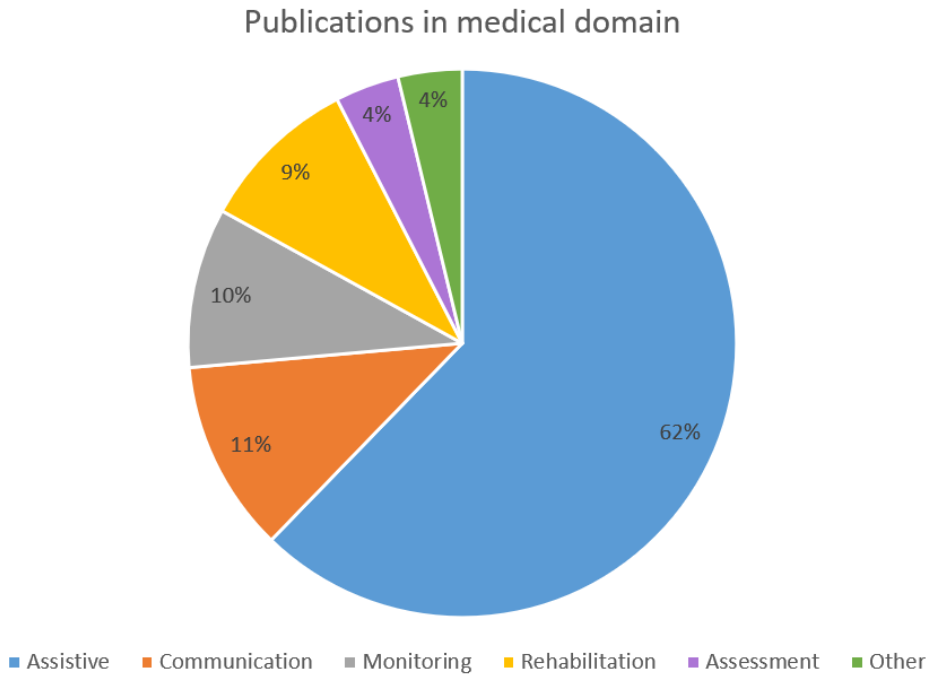

Figure 6: Distribution of publications in medical domain.

The largest field in the non-medical domain is monitoring contributing 50% of the articles in the non-medical domain. Additional two largest fields are control machine and entertainment contributing 17% and 16% of the publications respectively. Smaller coverage in the non-medical domain is by the publications in the field of assistive applications, authentication and communication each covering 2% of the publications. Different other types of publications cover the rest of 11% of the publications in the domain. When compared to previous similar studies Al-Nafjan et al. [13] has also noted that the majority of the publications in the non-medical domain concerning EEG-based BCI for emotion recognition has contributed to the monitoring field. The overview concerning the publications in the non-medical domain has been presented in Figure 7.

In the monitoring field there have been included all together 49 publications. The studies cover for example mental fatigue estimation [7], emotion recognition [23] and detecting meditation [18]. In the control machine field have been included the applications that able people to control via EEG different machines in their daily environment to make the life easier. These applications can be used for example for home appliance and smart home control [32], [33] or robotic systems [40]. EEG-based BCI applications are also used for entertainment such as live brain-computer cinema performance [211], driving car in a virtual city [9] or recommendations for music based on person´s mood [10]. Other applications include user authentication using visual stimuli of geometric shapes [8], messenger for smartphones [103], age and gender prediction [109] and other various possibilities.

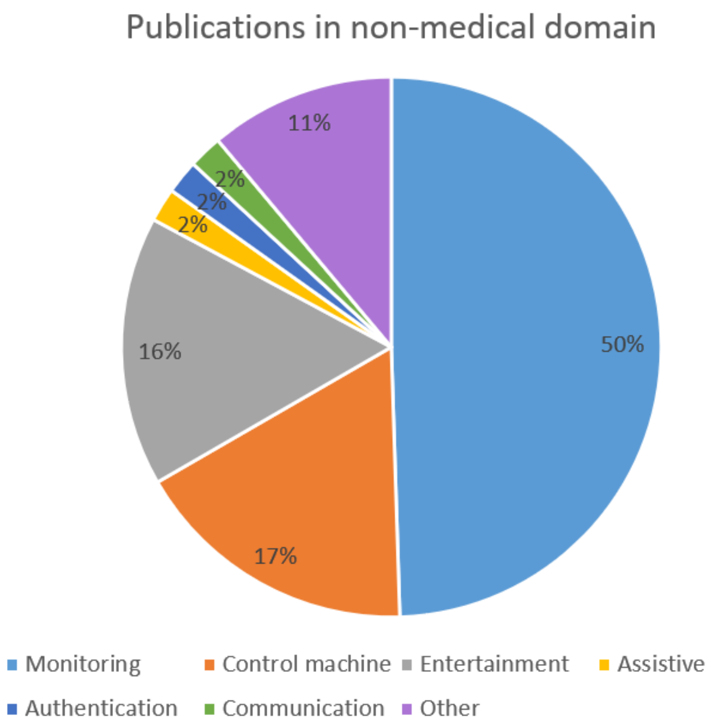

Figure 7: Distribution of publications in non-medical domain.

In smaller number of the publications both medical and non-medical domains have been covered. The domain has been further divided into fields communication, framework, assistive, control machine, monitoring and other as per type of publications. The details concerning distribution of publications covering both domains have been illustrated in Figure 8. Among studies covering both medical and non-medical field there is in 26% of the cases publications covering communication such as detection of imagined speech and classification of unspoken words from EEG signals [86], [87]. There are also 21% of the studies concerning framework such as developing new framework for practical BCI communication development [59].

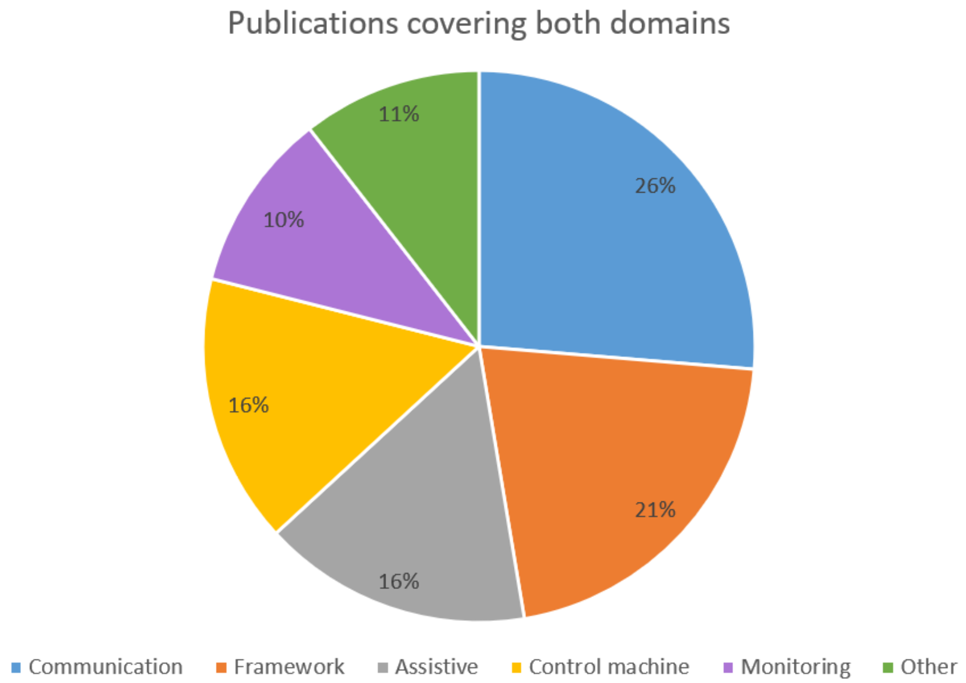

Figure 8: Distribution of publications covering both domains.

Assistive applications covering 16% of the studies include for example the control of robotic arms movement [52] and studies in the field of control machine covering also 16% of the studies include research for example on controlling a car in an experimental environment outside laboratory [36]. Additional studies have been focused on monitoring such as detection of kinesthetic attention [145]. Other fields covering for example development of serious games that could be used in entertainment, e-learning or medical applications [181].

5.5 Number of publications per author

The most productive authors concerning number of publications have been Abeer Al-Nafjan, Sravanth Ramakuri and Olga Sourina each publishing 3 publications as corresponding authors during the period from 2009 until 2019. Abeer Al-Nafjan (Imam Muhammad bin Saud University, Saudi Arabia) has published mainly experimental studies on classification of human emotions and monitoring emotional changes [45], [46] but has also published good systematic review concerning emotion recognition based on EEG-based BCI [13].

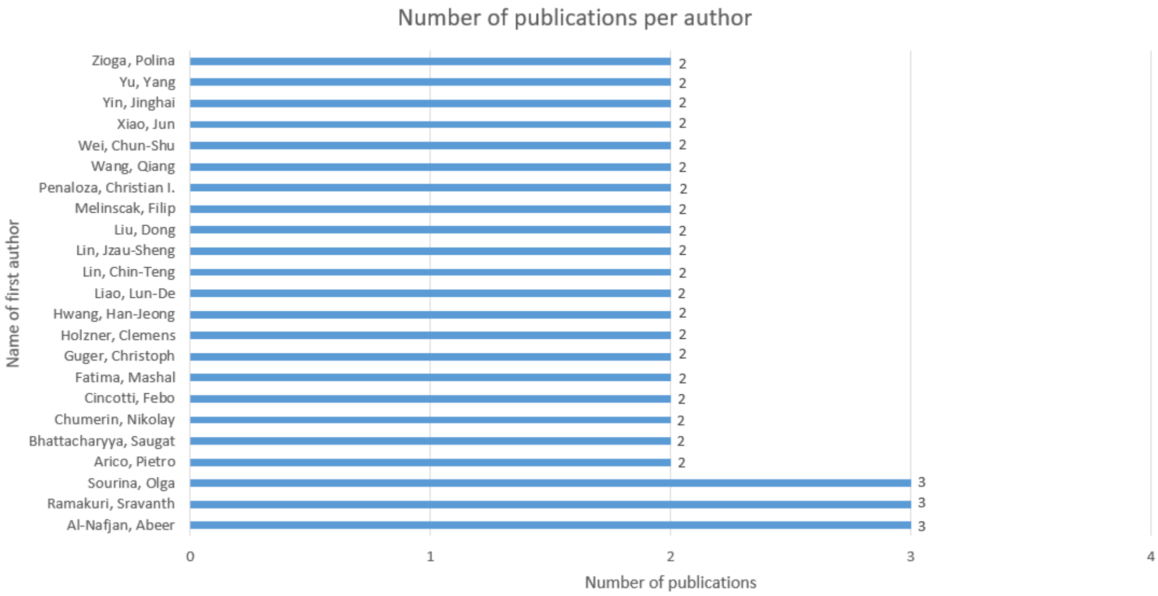

Figure 9: Number of publications per author.

Sravanth Ramakuri (Birla Institute of Technology, India) has published mainly experimental publications for example on human attention in the medical domain [17], [162] but has also published review article on behaviour state analysis through EEG-based BCI [20]. Olga Sourina (Nanyang Technological University, Singapore) has published on personalized digital experience, brain state and emotion recognition via BCI applications [173]–[175]. There are also 20 different authors who have published 2 publications as first authors on EEG-based BCI applications during the period. The detailed overview concerning the number of publications per author has been presented in Figure 9.

5.6 EEG devices used

Among studies analyzing EEG-based BCI applications most commonly used EEG devices are Emotiv EPOC from Emotiv, Quik-Cap from Compumedics Neuroscan and MindWave from NeuroSky. All together these three devices cover 57% of the publications on the topic. The most common EEG device Emotiv EPOC has been used in 40% of the publications analyzed when the prevalence of other popular EEG devices Quik-Cap and MindWave was 9% and 8% respectively. The high prevalence of Emotiv EPOC and Quik-Cap use among studies analyzing EEG-based BCI applications for emotion recognition has been noted also by Al-Nafjan et al. [13] and in general for EEG equipment by Roy et al. [14].

The most common EEG devices (Emotiv EPOC, Quik-Cap, MindWave) are all manufactured in USA. Other EEG devices used in the studies have been manufactured also in Germany (Easycap, actiCAP), Netherlands (Active Two), Spain (Enobio) and UK (MyndPlay BrainBandXL). The details of different EEG devices used, number of publications and percentage of publications covered has been shown in Table 7.

Table 7: EEG devices used in the publications.

EEG device	Number of publications	Percentage
Emotiv EPOC (Emotiv, USA)	31	40%
Quik-Cap (Compumedics Neuroscan, USA)	7	9%
MindWave (NeuroSky, USA)	6	8%
Electrodes	4	5%
Easycap (Easycap GmbH, Germany)	3	4%
actiCAP (Brain Products GmbH, Germany)	2	3%
Active Two (Biosemi, Netherlands)	2	3%
Enobio (Neuroelectrics, Spain)	2	3%
MyndPlay BrainBandXL (MyndPlay, UK)	2	3%
Other	17	22%
Multiple devices	1	1%

Emotiv EPOC and MindWave are considered to be low-cost consumer EEG devices when Quik-Cap is more expensive to purchase [14]. When Emotiv EPOC EEG device has 14 channels and MindWave 1 channel the Quik-Cap EEG device uses 32 channels. The cause of the general popularity of Emotiv EPOC EEG device would be due to the relative low cost of the device, sufficient number of EEG channels and the device considered easy to use. MindWave EEG device has limitations for use due to limited number of EEG channels, but the low cost and ease to use make the device still popular. The device could be applied in specific applications that do not require higher number of EEG channels. The Quik-Cap device on the other hand is more expensive, but has the advantage of higher number of EEG channels. The final decision concerning the use of specific EEG device depends on the type of EEG-based BCI application determining the need for specific number of EEG channels. The decision depends also on the cost planned for the study and devices for the end users.

5.7 Number of EEG channels

Among the studies analyzed the number of EEG channels used varies in large range. The highest number of EEG channels used was 163 by *Zhou* et al. for EEG-based classification of elbow versus shoulder torque intentions [208]. All together there were 5 studies (3% of studies) where more than 100 EEG channels were used indicating that the use of this high number of EEG channels is rather exceptional. Majority of the studies (64% of studies) involve 1-20 EEG channels, where 34% of the studies involve 1-10 EEG channels and 30% of the studies 11-20 EEG channels. There is also significant number of studies involving 21-40 EEG channels and 11 studies conducted with 61-70 EEG channels. The detailed overview concerning the number of EEG channels used in the studies has been given in Figure 10.

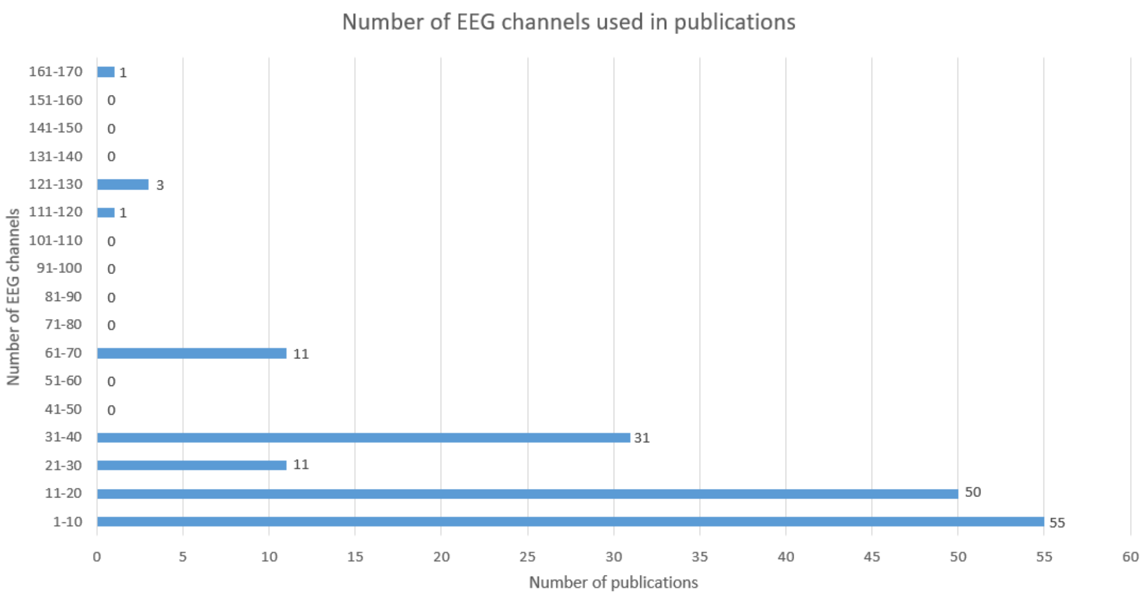

Figure 10: Number of EEG channels used in the publications.

Previously Roy et al. [14] have found that for obtaining EEG signals 1 to 256 electrodes have been used with half of the studies using between 8 to 62 electrodes. It was thought that very high number of electrodes does not give added value to the studies, more important is the exact location of smaller number of electrodes. In the article it was found that concerning the number of electrodes there is significant increase in sensitivity and specificity when increasing the number of channels up to 22, but further increase in the number of EEG channels would not give similar advantage.

Al-Nafjan et al. [13] have also concluded that the majority of studies use up to 64 channels for obtaining EEG data. In the study above by Al-Nafjan et al. it has been emphasized that when planning the use of specific number of EEG channels it is important to consider also the time required for the system setup, the comfort level for the subject and the number of features to be processed. When planning studies or developing applications for users it would be important to select the electrode positions carefully and limit the number of EEG channels used. Limited number of carefully selected electrode positions would make the future devices more user friendly and optimize the system performance.

5.8 Technique used to obtain EEG data

In the publications variety of techniques are used for the interaction between brain and computer in BCI applications. The most popular techniques include motor-imagery paradigm (applied in 38 publications), visual evoked potential paradigm (applied in 31 publications) and monitoring drowsiness/ attention (applied in 29 publications) or emotions/ affective states (applied in 15 publications). The overview concerning the prevalence of different techniques has been shown in Table 8. These techniques have been used all together in 73% of the publications reviewed where the technique used was stated.

Table 8: Techniques used in the publications.

Technique	Number of publications	Medical domain	Non-medical domain	Both domains
Motor-imagery	38	62%	24%	14%
Visual evoked potential	31	23%	61%	16%
Monitoring drowsiness/ attention	29	8%	88%	4%
Monitoring emotions/ affective states	15	7%	93%	0%
Auditory evoked potential	7	57%	43%	0%
Monitoring concentration	6	17%	50%	33%
Monitoring mental workload	4	0%	100%	0%
Vibrotactile evoked potential	3	100%	0%	0%
Imagined speech	2	0%	0%	100%
Error-related potential	2	0%	50%	50%
Multiple techniques	18	22%	67%	11%

Among the publications applying motor-imagery paradigm there were 62% of the publications in medical domain and 24% of the publications in non-medical domain. In addition to the aforementioned 14% of the publications covered both domain in one publication. Among the medical domain there are innovative applications such as EConHand [161], neuro-rehabilitation using virtual reality feedback [106] and intelligent brain-controlled robotic limbs [156], applying the motor-imagery paradigm.

In the visual evoked potential paradigm non-medical domain is dominant as 61% of the publications reviewed where the technique used was stated applied this technique. In the medical domain the prevalence of this type of technique used was 23% and both domains were included in 16% of the cases. Visual evoked potential paradigm is widespread among BCI applications as it has been long used and tested in high number of previous studies. The visual evoked potential paradigm involves also visual P300 paradigm and steady state visual evoked potential paradigm [1]. Among the most interesting applications of the aforementioned technique in the non-medical domain could be considered deceit identification test [76], use of EEG-based BCI devices to subliminally probe for information [84] and authentication based on emotionally significant images [164].

There is high popularity for monitoring the mind for drowsiness/ attention or emotions/ affective states. Both techniques use the analysis of changes in the EEG spectrum to determine the states and changes in one´s mind. The vast majority of the publications concerning drowsiness/ attention (88%) or emotions/ affective states (93%) are categorized in the non-medical domain. The monitoring of drowsiness/ attention based on EEG spectral changes has high practical value as there are number of studies implementing the technique in order to create helmet for on-site workers for drowsiness detection [31], predicting driver fatigue [132] or implementing EEG-based attention feedback in order to improve focus in e-learning [169].

The other techniques used in the publications are applied less frequently, but there is general trend noted in the overall use of various techniques. As in case of motor-imagery, auditory evoked potential and vibrotactile evoked potential technique the main application is in the medical domain, but the majority and larger variety of techniques are applied in non-medical domain. The trend indicates the high potential of non-medical applications for the EEG-based BCI applications. When taking into consideration that the majority of general population apply for non-medical domain vast number of people could benefit from this type of applications in the future.

5.9 Feature extraction

The feature extraction is an important processing step in order to extract the relevant details from the wide range of signals collected during obtaining the EEG data. In previous studies high number of different methods have been used for feature extraction. According to Al-Nafjan et al. [13] the feature extraction step is one of the major challenges in BCI systems and the technique is not optimal across different applications. The overview concerning the prevalence of different methods for feature extraction among the studies investigating EEG-based BCI applications has been presented in Table 9.

Table 9: Feature extraction used in the publications.

Feature extraction	Number of publications	Percentage
Power spectral density	23	18%
Fourier transform	20	16%
Common spatial pattern	18	14%
Wavelet transform	8	6%
Fractal dimension	7	6%
Independent component analysis	7	6%
Principal component analysis	7	6%
Autoregressive modeling	4	3%
Canonical correlation analysis	3	2%
Genetic algorithm	3	2%
Statistical features	3	2%
Other	10	8%
Multiple methods	13	10%

Among the studies reviewed the most frequently for the feature extraction were used analysis of power spectral density (used in 23 publications), Fourier transform (used in 20 publications) or the analysis of common spatial pattern (used in 18 publications). All together the aforementioned publications contribute to 48% of the publications reviewed. The results are similar to previous work from Al-Nafjan et al. [13] where it was shown that power spectral density and Fourier transform have been most frequently used for feature extraction in the studies to classify emotional features from EEG.

Other methods for feature extraction are used less frequently, but in many cases different feature extraction methods are used within one study. Similar general prevalence concerning the use of power spectral density and use of different feature extraction methods within studies has been noted by Al-Nafjan et al. [46], for analyzing human emotions from

EEG, Padfield et al. [2] when analyzing EEG-based BCI interfaces using motor-imagery technique and Sourina et al. [175] for real-time brain state recognition from EEG. The overall results correlate with previous studies in the field highlighting the importance of analyzing power spectral density, the use of Fourier transform and common spatial pattern for feature extraction and emphasizing the need to apply different types of feature extraction methods depending on the application under study.

5.10 Classification

During the classification different machine learning algorithms have been used in previous studies for EEG-based BCI applications. The most common machine learning algorithms used have been linear discriminant analysis and support vector machine that have been applied all together in 52% of the studies. When other machine learning algorithms have the coverage of 2-5% from all of the methods linear discriminant analysis has been applied in 31% of the cases and support vector machine in 21% of the studies.

Linear discriminant analysis has been characterized as simple classifier with low computation requirements and acceptable accuracy, support vector machine is a speedy classifier that supports binary and multi-class method and can perform linear and nonlinear modes [120]. Other methods applied in EEG-based BCI applications have been machine learning algorithms such as convolutional neural network, naive Bayes and random forest that contribute for 4-5% of the cases and artificial neural network, deep neural network, Gaussian mixed model and k-nearest neighbors that contribute for 2-3% of the cases. The overview concerning the classification methods has been given in Table 10.

Table 10: Classification used in the publications.

Classification	Number of publications	Percentage
Linear discriminant analysis	35	31%
Support vector machine	24	21%
Convolutional neural network	5	4%
Naive Bayes	4	4%
Random forest	4	4%
Artificial neural network	3	3%
Deep neural network	3	3%
Gaussian mixed model	2	2%
k-nearest neighbors	2	2%
Other	13	11%
Multiple methods	19	17%

The results of the current study are in correlation also with previous studies where Al-Nafjan et al. [13] have shown that the use of support vector machine is also one of the most popular method used for classification for EEG-based BCI systems for emotion recognition. According to aforementioned article the choice for classification algorithm depends on the type of brain signal being recorded and the type of application that is being controlled. Wide use of linear discriminant analysis and support vector machine for classification has been shown also by Padfield et al. [2] for EEG-based BCI-s using motor-imagery.

6. Discussion

In the first part of the chapter the trends in the publications concerning EEG-based BCI applications are discussed. In the second part of the chapter the current challenges hindering the development of the applications are highlighted and discussed to pinpoint the aspects that could need further effort in the future to resolve. In the last part of the chapter future possibilities are discussed in order to focus on the potential of the EEG-based BCI applications research field and the opportunities ahead. It is important to take into account the current trends, challenges and future possibilities in order to have better vision concerning the dynamics of the research field and better decisions for future development.

6.1 Trends in the publications

The current study has been divided into subsections based on the different aspects analyzed. The overall analysis starts with general overview of the articles and conference proceedings per year. It is seen that the overall number of articles and conference proceedings per year has been increasing. The increase in both articles and conference proceedings has been supported by the development of the technology making it easier to conduct research in the field of EEG-based BCI.

In the current study there have been included both articles and conference proceedings in order to reduce the possible effect of publication bias. It has been noted by Roy et al. [14] that higher variety of ideas are represented within different repositories and among different types of publications. It has been noted also in the current study that during the beginning of the period under review from 2009 there has been higher number of publications in the field of EEG-based BCI published as conference proceedings and over time the prevalence of articles has increased. The inclusion of both articles and conference proceedings in the analysis gives better representation of the ideas on the field throughout the period and helps to reduce any publication bias.

It is important to note that the majority of the publications (55%) contributed within the time period from 2009 to 2019 have been published in Asia. The most productive authors in the field of EEG-based BCI have been through the period Abeer Al-Nafjan from Saudi Arabia, Sravanth Ramakuri from India and Olga Sourina from Singapore. Asia has been in the lead role with most of the publications contributed per country by China. This is relevant finding as China has increasing influence in general in high technology sector and EEG-based BCI could be one important field of research resulting in high variety of high technology applications designed for many different fields of life both medical and non-medical. The high potential of EEG-based BCI applications and diverse possibilities for use could support in the future the economic strength of the countries and regions investing in the development and research in the field. In Europe all together 27% of the publications have been published followed by North-America with 13%. Among different regions of the world only from Africa no studies were published during the period under review.

The EEG-based BCI applications can be divided in two main categories medical and non-medical. Although the development of BCI applications has started historically from medical applications to support the communication and movement of patients in need the focus has spread among both medical and non-medical domains. With the development of the technology, reduction in cost and increase in comfortability of use the EEG-based BCI applications gain more and more attention in non-medical domain. In the non-medical domain applications have been developed for monitoring different states of the mind such as drowsiness on workplace or concentration during different tasks. Applications have developed in order to control machines and make people more efficient, for entertainment and many other tasks. EEG-based BCI applications have high variety of applications in both medical and non-medical domains with even higher potential nowadays in non-medical domain due to high number of potential users around the world.

Concerning technical aspects, the most commonly used EEG devices used for the BCI applications have been Emotiv EPOC from Emotiv, Quik-Cap from Compumedics Neuroscan and MindWave from NeuroSky. The three most common devices have been used all together in 57% of the publications, but Emotiv EPOC stands out from the three with prevalence of 40% among all publications on the topic. It is important to note that all three devices are manufactured in USA describing the importance of USA providing suitable equipment for the research in the field.

Among the studies under review 64% of them have applied 1-20 EEG channels. More specifically 34% of the studies have applied 1-10 EEG channels and 30% of the studies 11-20 EEG channels. The decision which EEG device to use and the number of EEG channels depends on the type of EEG-based BCI application. It has been found that overall high number of electrodes does not give added value, more important is the location of smaller number of electrodes [14]. When planning the selection of EEG device and number of channels it is important to consider the end users for the EEG-based BCI application that determines the technical requirements and possible cost of the device. Smaller number of carefully selected electrode positions would also make the device more user friendly and support performance of the system.

There is high number of possible techniques to use in order to obtain EEG data. The most popular techniques involve motor-imagery paradigm, visual evoked potential paradigm and monitoring drowsiness/ attention or emotions/ affective states via spectral changes in EEG. It is interesting to note that within the motor-imagery paradigm the majority of the publications have been in the medical domain whereas for other popular techniques majority of the applications have been created for non-medical purpose. The selection of the specific technique for obtaining EEG data is also highly dependent on the specific BCI application. As seen from the results of the current study highly diverse selection of techniques has been applied in the non-medical field supporting further the development of diverse applications in the non-medical field.

When selecting suitable technique for obtaining EEG data for specific BCI application one needs to also consider the most suitable method for feature extraction and classification. Overall there has been used most frequently analysis of power spectral density, Fourier transform or the analysis of common spatial pattern. During the classification most often linear discriminant analysis and support vector machine have been applied. Linear discriminant analysis is a simple classifier with low computation requirements, but acceptable accuracy, support vector machine has been characterized as a popular speedy classifier [120]. The prevalence of feature extraction and classification methods in the study corresponds to previous work by Al-Nafjan et al. [13], [46], Padfield et al. [2] and Sourina et al. [175]. The specific selection of the suitable method for feature extraction as well as for classification depends on the specific brain signal to be recorded and application under study.

6.2 Challenges

In the field of EEG-based BCI applications there is number of challenges hindering the development of the applications that would need to be addressed during further studies. It is important to acknowledge these aspects in order to find solutions or alternatives as needed. There are also many opportunities in the field to be used in the future and this is also important aspect to highlight and share ideas among researchers. The field has high potential and limitless possibilities. Sharing of new ideas and possibilities for the future facilitates further development of high variety of applications in the field of EEG-based BCI applications.

The challenges for the BCI applications could be divided as technology related or user related, where technology related challenges comprise of technical aspects and the usability of the system and the user related contain the aspects of person to learn to use the BCI application and subjectiveness of the person to interpret the cues given and generate or alter EEG signals required [13]. Padfield et al. [2] has categorized the possible challenges also as challenges faced in the research and development, challenges impeding commercialization, flawed testing process, issues with BCI use and ethical issues. The categorizations could be also combined and distinguish different technology related and user related challenges under the five categories proposed by Padfield et al. [2].

Concerning challenges the major aspect would be the current reliability of the BCI system in everyday noisy environments [88]. This hindrance affects both medical and non-medical applications, but higher effect is for the non-medical applications due to wider use outside of controlled environment. The effect on non-medical applications is also significant as the possible use of the EEG-based BCI applications in the non-medical domain would have even wider and number of users higher when compared to the applications used in the medical domain.

In the medical domain the challenges include in the assistive field low recognition rate for mental commands [156], problems with the signal acquisition equipment reliability and training process [21]. The character of the brain signals and the amplitude varies between persons which makes it also more difficult to develop BCI application well suitable to all patients [22]. The work on separating specific EEG signals from other signals [212] and the hindrances concerning the aspect of cross-subject classification [213] and accuracy of interpreting the commands [214] is ongoing. Authors agree that one of the important aspects is also the low throughput of information which may be limiting factor to some applications [21], [156]. The challenge of the low accuracy of the system has been experienced also in the field of monitoring emotional responses [159]. In the rehabilitation field the complexity of the system setup, expensiveness of the devices has been noted [161]. In neuro rehabilitation it has been highlighted that the therapeutic methods are hard to measure and the repetitiveness could be demotivating [106].

Concerning applications in the field of communication for patients it has been noted that the accurate classification of EEG signals has been hindered by the noise in the signals and low correlation detected between the signals and brain activities [207]. Depending on the language used the language itself could impose complications in the example Chinese Hanzi as the language contains more than 11000 characters which are difficult to display for the patient during the use of the potential BCI application [201].

In the non-medical domain for monitoring it has been emphasized that the convenience of the EEG device needs to be increase for the long-term wearing comfort [188]. There have been created for this reason also alternative devices to increase for example the user-friendliness of the devices meant to measure the drowsiness at work [31]. During detection of human emotions the hinderance could be the ambiguity of human emotions and the complexity of EEG signals [198]. There have been also conducted research on closed-loop interactions of human emotions with emotional stimuli for example in the case of music interface which complicates the system setup further [79]. In the field of entertainment it has been emphasized that the seamless interaction between user and the device is of utter importance and of main concern [110]. In addition to aforementioned constraints concerning signal quality and difficulty interpreting the actual commands and intentions BCI illiteracy has been also found as important aspect to consider. It has been estimated that approximately 20% of the BCI users are not able to operate the BCI application due to BCI illiteracy and additional significant proportion of the users use the system with suboptimal performance [157]. It would be important to further investigate the reasons behind the BCI illiteracy in order to determine possible solutions to overcome the hindrance.

Both medical and non-medical domain are affected by potential ethical issues in the EEG-based BCI applications filed of research. It would need to be determined for example who would be liable in case of any accidents during the use of BCI applications or could the applications affect for example user´s mood and therefore affect user´s decision making in wider sense [2]. It has been shown that under certain circumstances it would be possible to probe subliminally private information from the users using EEG-based BCI devices [84]. These aspects would need to be considered and the users notified concerning the possible risks and responsibilities.

With the widespread use of the devices the safety on individual and community level would need to be further analyzed. Nowadays it has been unfortunately common that due to security breaches malicious software has infiltrated to computer networks on high security level. This needs to be taken into consideration taken into account the sensitivity of the biomedical information obtained from the BCI device and also the potential possibility to alter the brain signals for example via neurofeedback. It has been hypothesized that for example the influence of the application on user´s mood could be used to alter user´s decision making for marketing or political agendas [2]. As the field of EEG-based BCI is quickly developing the ethical aspects would need to be analyzed and safeguarded in parallel with the development of the technology.

6.3 Future possibilities

With each new technology there are obstacles to overcome that could be achieved over time. Despite of the challenges faced in the field of EEG-based BCI applications there are many new possibilities for the future. In an ideal situation the EEG-based BCI application should be comfortable to use for longer period of time with seamless ease and function successfully in a noisy environment. The application should function well with different users without prior training. There is a way ahead to achieve these goals and for different EEG-based BCI applications the challenges and possibilities are different. Currently great progress has been made in order to increase the user-friendliness and breadth of use of the EEG-based BCI applications and bring them into our daily lives, but the full potential of the research field could be beyond our current imagination.

It has been suggested that in order to make the EEG-based BCI applications more accurate and efficient hybrid BCI systems should be developed that combine BCI system with another BCI or other kind of interface [2]. In addition to the use of only EEG for obtaining the biological signals other methods could be used to support the strength and quality of the signals such as fNIRS or fMRI [22]. Barrios et al. [37] has also suggested that combining fMRI with EEG could overcome significant limitations that are present with the use of EEG alone. Padfield et al. [2] has suggested to combine in hybrid BCI also different approaches using EEG such as motor-imagery system together with steady-state visually evoked potential as training aid or approaches combining different methods such as fNIRS combined with motor-imagery EEG or motor-imagery EEG combined with sensory interface.

In the medical domain the BCI could be used to control variety of assistive robotic devices. There has been developed EEG-based BCI applications for controlling wheelchairs [4], [195] and research has been done concerning of developing robotic limbs [156]. Further research could be done in order to apply also humanoid robots and drones for the support of daily activities for the patients [22].

It has been further suggested to use virtual reality in neuro rehabilitation, where motor-imagery BCI virtual reality systems could be used for real time applications for stroke rehabilitation to increase motivation of the patient during the rehabilitation process [106]. The monitoring of EEG could be used to enhance speech therapy sessions for people who stutter providing real-time visualization of the brain and insights concerning the brain activity during the sessions [45]. Jeunet et al. [29] have suggested BCI neurofeedback for the reducing hypokinetic activity in case of stroke and reducing hyperkinetic activity in case of attention deficit hyperactivity disorder (ADHD).

According to Abiri et al. [1] neurofeedback has been considered as one of the promising future directions for the EEG-based BCI applications. It is a process where the subject learns to self-regulate brainwaves in order to improve possible different aspects of the cognitive control. Abiri et al. have highlighted in the aforementioned work that neurofeedback has the potential to replace medications, alleviate neural diseases such as migraine, assist the treatment of persons with addiction, obesity, autism and astma or help patients suffering from ADHD, anxiety, epilepsy, Alzheimer´s disease, traumatic brain injury and post-traumatic stress disorder.

In non-medical domain there is high potential for the EEG-based BCI applications monitoring cognitive load, attention, drowsiness and other aspects of the mind. Monitoring cognitive load has been studied by Friedman et al. for intelligence tests, but measuring cognitive load could be used also to better design and conduct e-learning, psychometric exams, military training and other trainings [85]. It is important to analyze how the brain is involved in the tasks given and whether the tasks would be too hard or too easy for the participant to solve. Monitoring of the cognitive load could be used to adapt the difficulty or intensity of the training based on the subject in order the subject could apply optimal effort. In case the tasks would be too difficult the subject would not understand and learn and in case the tasks would be too easy the subject would be bored and the learning would be also suboptimal. Monitoring cognitive load could be also used for assessment to see how difficult would be certain task for different individuals.

There have been published several studies on monitoring attention via EEG-based BCI applications [17], [148], [169]. The level of attention is essential both in the learning process and during tasks with high responsibility. Sethi et al. [169] have developed EEG-based attention feedback to improve focus in e-learning, but the principles could be also applied for drivers to test their reflexes and attentiveness and for driving instructors to assess the capability of the drivers. The monitoring of attention level could be also used to correlate stress with attention level and creativity with attention level. According to Sethi et al. [169] for example optimal stress level can boost attention and with the help of monitoring attention optimal stress level could be determined when the attention level for the individual would be highest.

Drowsiness and fatigue detection have important practical implications for daily work for example in the field of construction, operating machinery and driving. In aforementioned cases drowsiness and fatigue can have serious or fatal consequences for the specific individuals themselves or the ones around them whether on the construction site or in traffic. For this reason many studies are addressing the problem and trying to find innovative solutions [7], [31], [188]. For the drowsiness detection of workers on site Dhole et al. [31] have proposed in addition to the current helmet solutions also the indoor positioning system, helmet to helmet communication and use of conductive EEG fabric instead of current solutions in use.

In other fields under non-medical domain there could be further development for controlling different machines. It has been suggested that control of machines and devices via EEG-based BCI could give new possibilities and increase the efficiency also for people without specific medical need. For example Penaloza et al. [156] has suggested further development of collaborative tasking and parallel multi-tasking where people could collaborate with the help of EEG-based BCI or could use for example additional robotic arm in addition to two biological arms.

EEG-based BCI applications could be further developed for wider authentication of persons in addition to currently available methods [8]. Authentication via EEG has several advantages when compared to current methods. In case of current traditional authentication methods such as passwords or biometric authentication via fingerprints EEG based authentication would be much safer and harder to copy. Passwords could be easily copied and used, but it is much more complicated to copy person´s EEG and present for authentication. In case of using fingerprints the biometric data could be stolen and used by other persons for authentication with no possibility for the actual person to change the biometric details. In case of EEG-based authentication the data is difficult to copy and the biometric data for authentication could be changed via thinking about another element in case needed.

It has been suggested that EEG data could be used also for deceit identification. As polygraphy test is not fully reliable and the results could be altered in case of specific practice and training by the subject EEG data could be important alternative for deceit identification in the future [76]. Punsawad et al. [159] have suggested that the monitoring of human emotions via EEG-based BCI application could be applied in neuromarketing for product branding and advertising slogan design.

Developing field is also entertainment which includes for example gaming. The availability and user friendliness of the games using EEG-based BCI is increasing with time [110]. With further development of the technology and integration with currently available technological possibilities there are numerous possibilities for the use of EEG-based BCI for games for both entertainment and serious games for training purposes [24]. EEG-based BCI technology could further merge with virtual reality giving additional dimension for the EEG-based BCI applications. Further development and use of virtual reality would support the use of EEG-based BCI applications in many fields including games and also art [2].

In case a person is able to receive feedback concerning one´s own emotions or other mental states in real-time and make changes to the mental states at one´s will EEG-based BCI applications could be used for triggering awareness about oneself and facilitate learning and enhance brain functionality [79]. The benefit of EEG-based BCI applications could be also applied via neurofeedback for sport motor skills improvement, acting skills improvement or surgical skills improvement [29].

In order to facilitate further development of the EEG-based BCI applications it would be important to make the applications and devices more user-friendly, reliable and corresponding to user needs. In both medical and non-medical domain it has been suggested that the use of dry electrodes should be preferred in order to increase the user-friendliness of the devices [161]. It is also important to conduct the research under realistic conditions for applications and devices to work properly outside of the controlled environment in everyday situations [30].

During the daily use of EEG-based BCI applications the safety of the use is one of the most important aspect to focus. In case of synchronous BCI the controlling of the BCI is divided into time windows when the commands by the user could be given and the transfer of commands from the user to the device is well defined. For the user asynchronous BCI applications would be preferred as in case of asynchronous applications the commands could be given to the device at every time not depending on specific time windows. From the safety aspect it is important to define for the device in case of asynchronous devices when the user actually wanted to give command and when the user was thinking other thoughts not related to the use of the device. For this reason the concept of "brain switch" would need to be further developed in practice enabling the user to mentally disconnect from the device when the user is not intending to use the device [22], [129].

Further possibilities include for the EEG-based BCI applications new more convenient methods for obtaining EEG signals. Wei et al. [188] has suggested measuring of EEG from non-hairbearing scalp areas for the further ease of use during long-term use of the EEG-based BCI devices in everyday situations. It has been also shown that in some cases it would be sufficient to measure EEG only near the ear that could make the use of EEG-based BCI applications more convenient [112]. In order to make the use of BCI applications more efficient and further integrate the possibilities into our daily tasks BCI-s could be integrated with augmented reality which would create new dimensions of user experience and practicality [32].

Summary

EEG-based BCI applications has been quickly developing field of research due to the high potential of use for variety of tasks. Although the initial need for the EEG-based BCI applications has come from medical domain the possibilities for use have spread much wider and have the potential to be incorporated in many aspects of our daily lives. In addition to the initial applications supporting communication and movement of patients in medical setting EEG-based BCI applications also support healthy persons to become more efficient via innovative use of machines or devices, monitoring drowsiness in order to increase safety on workplace, providing neurofeedback to support concentration and in high number of other aspects.

Therefore it is important to analyze the trends in the EEG-based BCI applications field of research in order to have overview concerning the trends in the research and analyze the studies conducted in medical and non-medical domain. The previously conducted studies in medical and non-medical domain are further divided into fields of research and analyzed within these domains. Also overview has been given concerning the use of equipment and signal processing.

The systematic literature review has been prepared following the PRISMA model developed by Moher et al. The model gives structured method and collection of principles for preparing and conducting the systematic literature review. During the process three well known databases PubMed, Scopus and Web of Science were selected to conduct the publication search. The search resulted in 1205 publications from which duplicates were removed and 635 unique publications further screened and assessed for eligibility. After assessment 202 eligible publications were included in the final analysis.

The overall number of articles and conference proceedings has been increasing throughout the years. The increase in research has been supported by the development of the technology making it easier to conduct the research in the field. The majority of the research has been done in Asia with China contributing the highest number of publications throughout the years.

With the development of the technology, reduction of cost and increase in comfortability of the devices more attention is focusing in the non-medical field. In addition to the applications in the medical domain such as systems for communication for patients in

completely locked-in state and support for rehabilitation of stroke patients applications have been developed to control machines and devices such as robotic limbs, humanoid robots, drones and smart home applications. The aforementioned examples are only few possibilities and the number of overall possibilities for the EEG-based BCI applications in medical and non-medical domain is limitless.

The currently most commonly used devices for EEG-based BCI applications are Emotiv EPOC from Emotiv, Quik-Cap from Compumedics Neuroscan and MindWave from NeuroSky all manufactured in USA. The number of EEG channels in use varies from 1 to 163 with majority of the studies involving up to 20 EEG channels. Concerning signal analysis the most popular technique use to obtain EEG data involves motor-imagery paradigm. For feature extraction analysis of power spectral density has been most frequently used and for classification linear discriminant analysis, simple classifier with low computation requirements, has been applied. The specific selection of the device and signal analysis methods depends on the signal recorded and application under study.

Concerning challenges the EEG-based BCI applications are working better in controlled environment, but would need to have more reliability in everyday noisy environments. This aspect affects applications in both medical and non-medical domain, but would have bigger impact for non-medical domain as the applications in the non-medical domain would need to be able to endure more diverse environments. The accuracy of interpreting the commands and the adaptability with different users needs to be further increased for the applications. One of the most important hindrance to address is the user-friendliness and comfortability of the devices.

In addition to the specific challenges with the applications and devices also the potential ethical issues need to be considered when implementing broader use of EEG-based BCI applications. Ethical considerations would include the question concerning liability in case of accidents, but also the possibility of the application to affect user´s mood and decision making process. Also the aspects of data privacy and information security need to be ensured as sensitive biomedical data is collected by the devices.

Although there are certain challenges in the field of EEG-based BCI applications the possibilities for the future are vast. In order to increase signal accuracy, the use of hybrid BCI-s has been suggested. Hybrid BCI-s would combine BCI system with other BCI system or other kind of interface. Use of fNIRS and fMRI has been also suggested in addition to

EEG. In order to make the devices more comfortable during long-term use it has been suggested to use non-hairbearing scalp areas for obtaining EEG signal. It has been also suggested that for certain applications it would be sufficient to measure EEG only near the ear, which would make the use of EEG-based BCI applications more convenient.

Current systematic literature on EEG-based BCI applications has analyzed the articles and conference proceedings published on the topic during the period from 2009 until 2019 according to the objectives determined for the study. The aforementioned field of research has high potential and diverse possibilities for providing applications to support patients in need and enabling healthy persons to be more efficient, collaborate, develop themselves and much more.

Acknowledgement

I would like to thank my thesis supervisors Yar Muhammad (PhD) and Naveed Muhammad (PhD) from the Institute of Computer Science at University of Tartu for continuous support during the planning and conduct of the systematic literature review. The discussions and advice during the process have been valuable support for selecting the best methods, conducting the review process and obtaining the results.

I would also like to thank the personnel from University of Tartu Library especially Signe Bachmann for advice and assistance for obtaining articles and conference proceedings needed for the preparation of the thesis. I want to thank also the authors of the publications analyzed in the literature review for providing articles and conference proceedings from their side in case needed. The conduct of the systematic literature review would not have been possible without this good collaboration from all involved. Thank you.

Kaido Värbu

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